Values of Time for Carpool Commuting: A Discrete Choice Experiment

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INTRODUCTION

Traffic congestion is still a major issue in large cities around the world. France is no exception to this observation. According to INRIX (2018), the drivers in Paris, Marseille, Lyon and Toulouse – the four largest cities in the country – respectively lost on average 237, 140, 141 and 130 hours in road congestion in 2018. Most of this traffic congestion appears during morning and evening peak hours.

Promoting carpool is seen as a cost-effective way to moderate road congestion and gas emissions. The objective is to increase cars occupancy rate. There is a clear room for improvement as the current rate is low, between 1.2 and 1.3 individuals per vehicle on average for weekday trips following French National Transport and Trips Survey (ENTD, 2008). This occupation rate falls at 1.08 for commuting trips. It implies that there is a large unused transport capacity during peak hours.

Local policy makers in France currently consider different kinds of policies to promote carpool for commuting trips. The cities of Lyon and Grenoble will experiment HOV lanes in 2020. These lanes are expected to reduce travel time and to increase travel time reliability for carpoolers. The Ile-de-France (Paris) Region gives monetary incentives to carpool drivers (between 1.5 and 3 euros per trip), and free public transport tickets for carpool passengers. Several regions developed a carpool web platform to make the matching between drivers and passengers easier. Private companies are also encouraging their employees to carpool. Moreover, Vinci, a motorway company, has launched a partnership with Blablacar, the world number one carpool company (see Shaheen et al. 2017). Vinci's subscribers carpooling on the motorway benefit from lower management fees on the BlaBlaCar platform .

The number of commuters being equal, reducing congestion imposes to reduce vehicle traffic and consequently to higher the occupancy rate in vehicles. Hence, a key element to reduce congestion is to convince a part of the solo drivers to become carpool passengers. All these policies could be sharpened with a better understanding and measure of carpool trips attributes. In a state-of-the-art of ridesharing[2], Furuhata et al. (2013) emphasize how route and time matching issues between drivers and passengers can be very constraining, even in a simple situation. They also identify different classes of carpools/rideshares and hence different constraints and/or advantages for each one. Chaube et al. (2010) conducted a survey in an American university and found that a close relationship was a key factor of successful ride-matching: 98% of students would accept to carpool with a friend, 69% with a friend of a friend, but only 7% would accept a ride with a person they do not know. Gender and age differences in the car party are also issues involved. However, in spite of several studies identifying obstacles to carpool, we did not find evidences of carpool-specific values of travel time in the literature.

This paper aims to fill this gap. We address the following research questions: what are the values of the time components of a commuting trip (in-vehicle travel time, travel time variability, waiting time, access or detour to carpool meeting place, egress) made as a carpool driver or passenger? Are these values different from the values for a trip made as a solo driver of a public transport user? How are the values distributed across the commuter population?

We respond to these questions by measuring values of these time components for a commuting trip as a solo driver, as a carpool driver, as a carpool passenger and as a public transport passenger. To this aim, a stated choice experiment survey was conducted on a sample of 1735 commuters using their car to commute in the city of Lyon.

Results are of interest for several reasons. First, they bring information to improve policies promoting carpool such as HOV-lane and carpool driver or passenger subsidy. Second, our estimations of carpool-

[2] In the following we use indifferently "carpooling" or "ridesharing"

specific components values can be used in transport forecasting models. They could also be used as prior values to establish official guidelines in CBA. Finally, carpool matching platforms could be interested in our estimations and in our latent class models to implement market differentiation.

METHODOLOGY

The questionnaire is organized in three parts. The first part aims at collecting basic socio-demographic data and the trip characteristics. The second part is the stated choice experiment. It is a dynamic experiment in the sense that the choices tasks proposed to the respondent depend on her trip characteristics. The third part is a questionnaire on attitudes.

We first collect information on socio-economics variables of the respondent (gender, age, income, professional position…) and on the characteristics of their "usual trip" i.e. the most frequent trip made by public transport or car. These characteristics will be used to dynamically build the choice tasks in the second step of the survey.

The sample is randomly split out into two subsamples to measure the effect of the carpool organization (planned or spontaneous) as presented in Figure 1. Each sub-sample see a different screen. Individuals in the "planned organization" sample see a screen where carpool is presented as organized.[3] Individuals in the "spontaneous organization" sample see a screen where carpool is presented as spontaneous.[4]

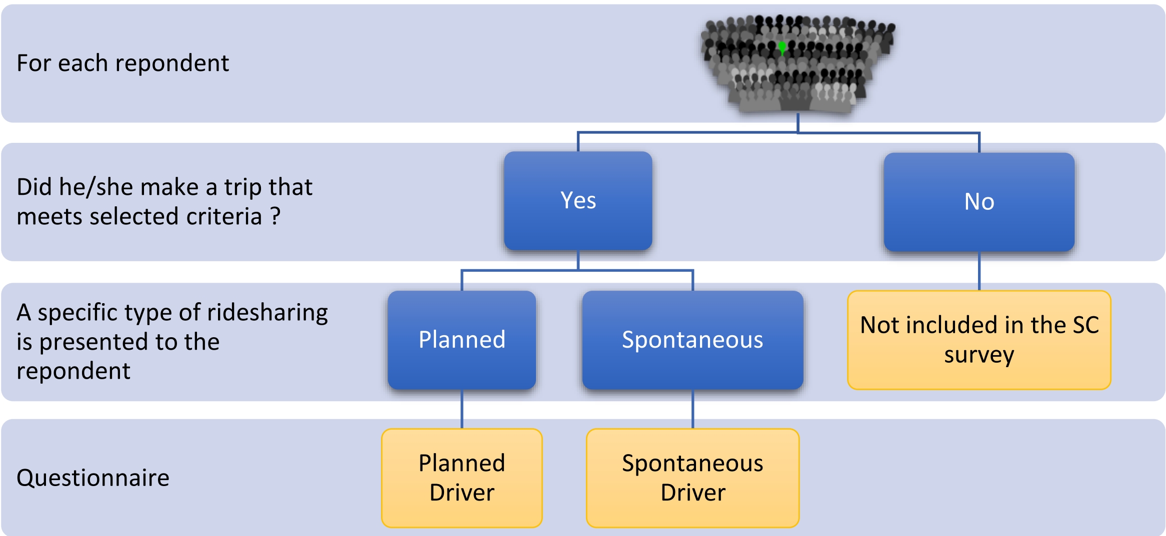

Figure 1: Data sampling and survey protocol

For a given trip, each alternative is characterized by 2 types of variables. Time variables, including the various time components of the trip. And monetary aspects. These 2 variables are classic attributes of mode choice in transport economics. In carpool alternatives, matched carpooler's profile is also presented. Even though these variables are expected to affect mode choice, we will mainly focus on time and monetary aspects in this paper.

[3] Organized carpool implies arranged place and time schedule. It can be organized by carpooling platforms or informal with family, friends or colleagues.
[4] Carpoolers can meet up in a carpool station or along the road. This involves hitchhiking and so-called dynamic carpooling through digital apps.

Figure 2: An example of choice screen for a driver respondent with a 8:30 preferred arrival time

Mode	Driver Alone	Driver in a Carpool	Passenger in a Carpool	Public Transport
Trip Characteristics	Start : **7:20** Drive Alone: Between **30** and **40 min** Arrival: Between **7:50** and **8:00**	Start : **7:30** Join the station: **no** detour Wait: **5 min** Carpool : Between **25** and **40 min** Join your destination: **5 min** walk Arrival : Between **8:15** and **8:30**	Start : **7:35** Join the station: **5 min** walk Wait: **5 min** Carpool : Between **30** and **40 min** Join your destination: **5 min** walk Arrival : Between **8:20** and **8:30**	Start : **7:30** Join the station: **10 min** by car Wait: **5 min** Public Transport: Between **25** and **40 min** Join your destination: **5 min** walk Arrival : Between **8:15** and **8:30**
Monetary aspects	You pay your usual transportation costs	You pay your usual transportation costs Carpooling makes you earn 1€	You save on your usual transportation costs Carpooling costs you 1€	You save on your usual transportation costs Public Transport costs you 0,80€
Carpooler's profile		Your passenger: 45 years old, Hitchhiker	Your driver: 25 years old, Referenced on the carpool platform	
Which mode do you choose ?	○	○	○	○

Finally, five questions are asked to evaluate the respondent's sensitivity to environmental consequences of the solo driving practice. Following Wall et al. (2007) conclusions we build a set of five statements presented on a Likert scale.

In this paper, the focus is on the valuation of different time variables presented to the respondent. We use a willingness to pay space (WTP) utility specification as presented first by Train and Weeks (2005). This expression of the utility is a re-parametrization, multiplying the cost estimate by others estimates for time variables we want to value. This specification allows for a direct interpretation of time estimates as values of time. It will also make the estimation of values of time easier in mixed models as we will see in the next section.

As an example, we focus on the utility a **carpooling passenger** experiences:

$$\begin{aligned} V_{PCarpool} &= \beta_{0pcp} + \beta_{\mathrm{spontpcp}} Spont + \beta_{\mathrm{cost}} \times \\ &(Cost + \beta_{\mathrm{ttpcp}} TT + \beta_{\mathrm{ttvpcp}} TTV + \beta_{\mathrm{waitpcp}} Wait + \beta_{\mathrm{access}} Access + \beta_{\mathrm{egress}} Egress + Spont \\ &\qquad \times (\beta_{\mathrm{ttspcp}} TT + \beta_{\mathrm{ttvspcp}} TTV + \beta_{\mathrm{spontwt}} Wait)) \end{aligned} \tag{3}$$

Where $Cost$ is the cost attribute, TT is the in-vehicle travel time, TTV represents travel time variability and $Wait$ is the waiting time. $Spont$ is a dummy coded variable indicating if the respondent answered choice tasks with spontaneous carpooling ($Spont = 1$), or planned carpooling ($Spont = 0$). This variable is here to check for differences in sensitivities between the two carpool organization types $Access$ and $Egress$ are respectively access and egress times experienced by the passenger. These variables are categorical. We check the sensitivity difference between an access to the carpool station by walk (reference) versus an access by car. In the same vein, we measure the impact of an egress by public transport versus an egress walking (reference).

Utility functions for other modes are analogous.

To analyze this discrete choice data, we will use the 3 main models found in the literature of choice modeling. The simple multinomial logit which is the usual base model. Two other models capable of modelling individual heterogeneity in sensitivities for some attributes as mentioned in Lancsar et al. (2017): the latent class logit, and the mixed logit model, to account for the panel structure of the data. We will compare results of these 3 models in the next section.

RESULTS AND DISCUSSION

In the MXL model, all random time coefficients are estimated with a lognormal distribution. This way, coefficients cannot change sign and the problematic case of negative values of time is avoided (Hess et al. 2010). Access and egress variables are let as fixed parameters since their standard deviation are not significant when they are randomly distributed. Constant are also estimated as random parameters, following a normal distribution.

In the LCL model, four latent classes were selected as the best fit from 2 to 5 classes models tested. Estimating socio-economic variables (gender, age and income) as latent class membership covariates was inconclusive. The five “attitude statements” performed better.

Finally, some control variables are added to check for differences in values of time between the “planned” and the “spontaneous” carpool organizations.

Values of time are summarized in Table 1. Values for MXL are the median of conditional distribution (see Train 2009). Median values are shown rather than mean as lognormal distributions have a long righthand tail.

Table 1: Values of Time (in €/h)

Attribute	Alternative	MNL	MXL	LCL			
				Class A	Class B	Class C	Class D
In vehicle travel time	Driver Solo	21.6	36.5 [22.2, 51.6]	36.5	9.5	43.1	13.0
	Driver Carpool	37.0	34.0 [31.4, 35.5]	20.6	23.8	49.0	30.8
	Passenger Carpool	24.2	27.1 [25.0, 28.2]	23.0	5.4(ns)	42.1	11.9(ns)
	Public Transport	27.2	32.5 [29.9, 33.6]	27.0	16.2	39.7	7.8(ns)
Travel time variability	Driver Solo	11.7	16.4 [6.0, 42.0]	0.5(ns)	11.7	3.6(ns)	12.3
	Driver Carpool	17.6	19.0 [16.5, 20.6]	14.6(ns)	10.9	33.7	-0.2(ns)
	Passenger Carpool	37.1	31.5 [30.3, 32.3]	11.7(ns)	35.8	34.2	10.9
	Public Transport	28.0	31.2 [29.2, 32.5]	18.2	18.1(ns)	39.9	24.0
Schedule late	Driver Solo	2.5	4.8 [4.0, 5.6]	-2.4(ns)	-3.2	4.9	-0.3(ns)
Schedule early	Driver Solo	12.7	16.1 [12.8, 18.6]	19.0	7.9	23.8	9.8
Detour time	Driver Carpool	37.4	35.2 [31.9,37.9]	7.8(ns)	25.1	59.1	41.1
Waiting time	Driver Carpool	48.2	43.2 [40.5, 45.6]	53.7	40.5	50.4	24.1
	Passenger Carpool	62.8	39.1 [28.7, 48.5]	29.1(ns)	25.3(ns)	25.4	6.4(ns)
	Public Transport	44.6	32.5 [31.0, 33.8]	9.7(ns)	49.8	47.3	28.8(ns)
Access time 10*	Passenger modes	4.6	2.6	3.2			
Access time 20*	Passenger modes	10.7	8.4	10.6			
Egress time 10*	Passenger Carpool	7.1	4.6	5.6			
Egress time 20*	Passenger Carpool	4.7	2.3	1.3(ns)			

Notes: This table reports MNL, MXL and LCL estimates of values of time. (ns): Non-95%-significant values.
**Since Access and Egress time are dummy coded, values in the Table represents the monetary value compared to the reference situation: 5 min walk.*
Values for MXL are the median values of the lognormal distribution estimated. IQR in brackets [Q1, Q3].

Table 2: Monetary equivalents of alternative specific constants

Attribute	Alternative	MNL	MXL	LCL			
				Class A	Class B	Class C	Class D
Constants	Driver Carpool	6.3	-5.9[-10.6, -1.5]	-24.4	16.2	14.3	-22.0
	Passenger Carpool	-4.9	-14.2[-14.2, -14.2]	-23.3	-5.4(ns)	6.4	-40.8
	Public Transport	-5.5	-14.3[-18.5, -10.4]	2.6(ns)	-11.8	5.5	-36.3

<u>Constants</u>

Constants have a tremendous impact on utilities. They have a negative impact on the alternative modes to solo driver and reveal pure preferences for some modes in the different classes of the LCL. They can be assessed with their monetary equivalent (see Table 2).

Furthermore, they can also explain why some classes have several non-significant variables. Taking the example of class D in LCL, constants have such a huge monetary impact (in favor of driving solo) that this class does not even consider some attributes from alternative modes to driver solo.

<u>In vehicle travel time</u>

Overall, InVoTTS values we find for all modes are higher than what Wardman et al. (2016) and Shires & De Jong (2009) found for commuting by car in France, respectively 11.8€$_{2019}$/h and 15.4€$_{2019}$/h.

Several reasons may explain this. First, our sample is composed of currently solo drivers, who may have higher incomes than the whole population and hence higher values of time. Another explanation could be that these values could be considered from a willingness to accept (WTA) perspective since through the exercises it is asked what the solo driver is willing to accept to switch to another mode. In the InVoTTS field, De Borger and Forsgerau (2008) found an important gap between WTP and WTA with a 1 to 4 factor.

Although our sample is composed of current solo drivers, InVoTTS for solo driver mode is found higher than for alternative modes. In solo driver mode, waiting time, access time and egress time are null. Thus, these results are still consistent with the preference for the solo driver mode hypothesis. To ensure this, a new model will be considered with “total travel time” (including all time components). Results will be compared with these presented here.

Travel time variability

Uncertain time expected in carpool or public transport is valued higher, with an increase of 50% of InVoTTS for drivers to 100% for passenger modes. These estimates may absorb a lacking comfort effect. We can also suppose individuals may feel more in control when driving than in passenger situations.

Schedule delay

The schedule late delay is valued lower than schedule early delay. This result is unexpected and may be a misunderstanding of the schedule delay variable by the respondent. This effect could be explained because respondents may saw their departure time was later than usual and hence thought their total travel time was lower. We can also assume respondents may have flexible schedule.

Waiting time

These values are overall valued higher than InVoTTS, confirming what past studies found on the topic (see Wardman, 2016). The flatter distribution for carpool passengers in MXL can be attributed to uncertainty. Giving the fact that carpool may be perceived less reliable than public transport, the passenger could wonder if his/her driver will finally come.

Detour time

We can interpret from these values detour time for a driver is not valued significantly different from the in-vehicle travel time but still barely lower than waiting times.

Access and egress time

Our 20-minute egress time is overall valued lower than our 10-minute egress time. This surprising result may be the consequence of our survey design, which was D-efficient. We maybe lacked good priors for some value of time attributes and an optimal design could have solve this issue. The egress20 variable was often present at the same time than the access20 variable. It explains why the models underestimate the effect of this variable (and hence, maybe overestimate for a bit the access20 effect). Nevertheless, we can still note a higher value for a 10-minute egress time in public transport than its equivalent for access by car, which could mean that an arrival close to the final destination is more important than a departure close to the domicile for an individual.

6. CONCLUSION

This paper valued various time attributes of 4 modes (solo driver, carpool driver, carpool passenger and public transport) for commuting trips. A stated choice survey conducted on a 1735-respondent sample allowed us to explain modal choices through two different models allowing for heterogeneous tastes: mixed multinomial and latent class logits.

The originality of this paper is the focus on various carpool specific values of time for daily trips, both as a driver and as a passenger. A comparison of these values is also provided with more classic modes found in the literature: solo driving and public transport.

Moreover, these time values seem insufficient to completely explain modal choices as our constant values are high and thus explain substantially mode preferences. This suggests time gains provided by a HOV lane may not be enough to convert some currently solo drivers into future carpool passengers. Maybe financial incentives will be needed. Our sample also react differently through the attitude statements. Hence, incentives may also adapt to target different parts of the population.

Finally, we find spontaneous carpool specific effect need to be confirmed through further research.

REFERENCES

Chaube, V., Kavanaugh, A. L., & Perez-Quinones, M. A. Leveraging social networks to embed trust in rideshare programs. In *2010 43rd Hawaii International Conference on System Sciences*, 2010. 1-8. IEEE.

De Borger, B., & Fosgerau, M. (2008). The trade-off between money and travel time: A test of the theory of reference-dependent preferences. *Journal of urban economics*, *64*(1), 101-115.

ENTD, 2008. Enquête nationale transport et déplacements.

Furuhata, M., Dessouky, M., Ordóñez, F., Brunet, M. E., Wang, X., & Koenig, S. Ridesharing: The state-of-the-art and future directions. *Transportation Research Part B: Methodological*, 2013. 57: 28-46.

Hess, S., Bierlaire, M., Polak, J. (2010). Estimation of value-of-time using Mixed Logit models.

Louviere, J. J., Hensher, D. A., & Swait, J. D. *Stated choice methods: analysis and applications*. Cambridge university press, 2000.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.

Shaheen, S., Stocker, A. & Mundler, M. (2017) Online and app-based carpooling in France: Analyzing users and practices - A study of BlaBlaCar. Disrupting Mobility, 181 – 196

Shires, J. D., & De Jong, G. C. (2009). An international meta-analysis of values of travel time savings. Evaluation and program planning, 32(4), 315-325.

Train, K., Weeks, M. (2005) Discrete choice models in preference space and willingness-to-pay space. In: Application of Simulation Methods in Environmental and Resource Economics, chap. 1, 1 – 16

Wall, R., Devine-Wright, P., Mill, G., 2007. Comparing and Combining Theories to Explain Proenvironmental Intentions. The Case of Commuting-Mode Choice. *Environment and Behavior*, Volume 39 Number 6.

Wardman, M., Chintakayala, V. P. K., & de Jong, G. (2016). Values of travel time in Europe: Review and meta-analysis. Transportation Research Part A: Policy and Practice, 94, 93-111.